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(54) **METHOD AND SYSTEM FOR CONTROLLING A DEXTEROUS ROBOT EXECUTION SEQUENCE USING STATE CLASSIFICATION**

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USPC **700/258**; 700/246; 700/247; 700/260; 700/261; 700/262; 700/263; 700/264

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See application file for complete search history.

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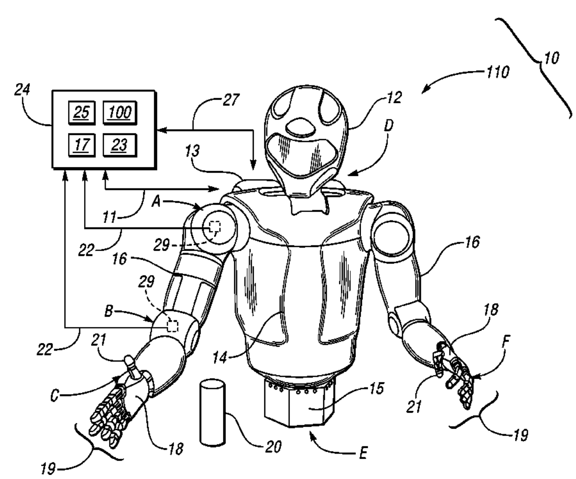
(57) **ABSTRACT**

A robotic system includes a dexterous robot and a controller. The robot includes a plurality of robotic joints, actuators for moving the joints, and sensors for measuring a characteristic of the joints, and for transmitting the characteristics as sensor signals. The controller receives the sensor signals, and is configured for executing instructions from memory, classifying the sensor signals into distinct classes via the state classification module, monitoring a system state of the robot using the classes, and controlling the robot in the execution of alternative work tasks based on the system state. A method for controlling the robot in the above system includes receiving the signals via the controller, classifying the signals using the state classification module, monitoring the present system state of the robot using the classes, and controlling the robot in the execution of alternative work tasks based on the present system state.

15 Claims, 2 Drawing Sheets



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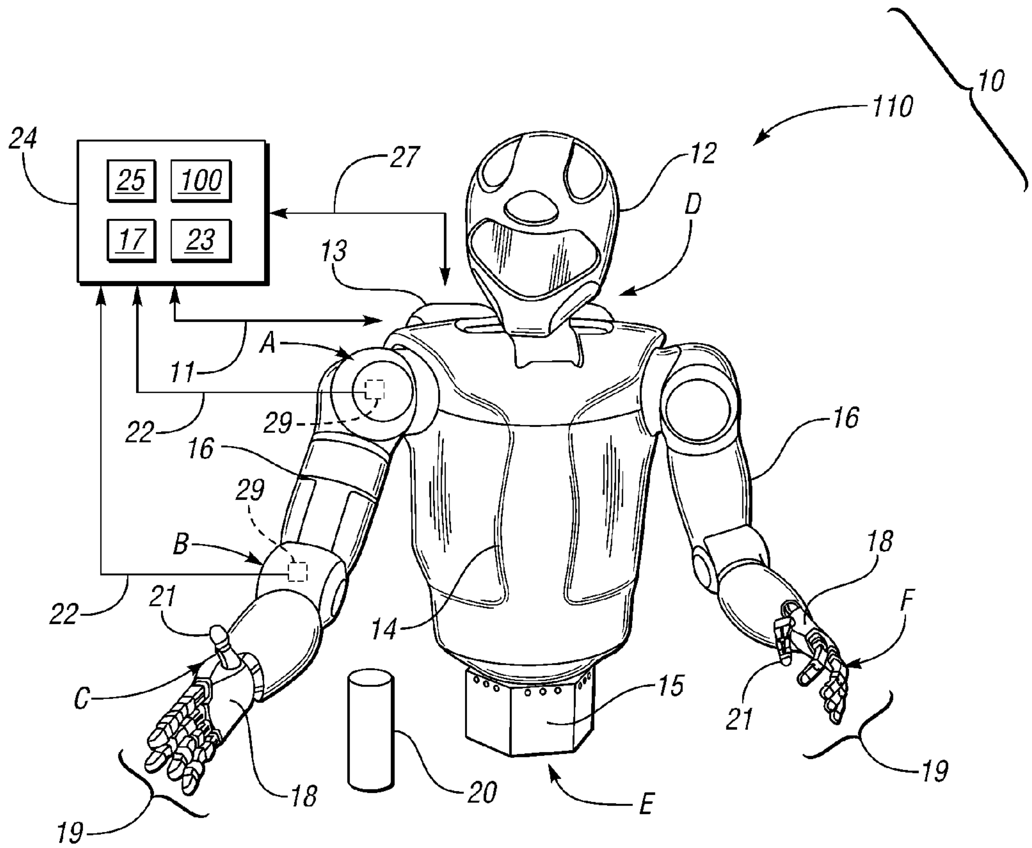
10
110
24
25
100
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A
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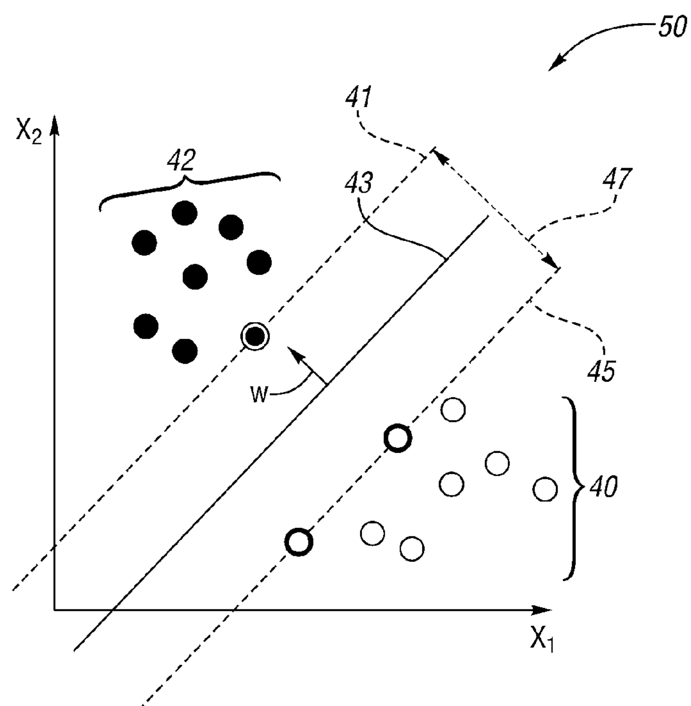
FIG. 1


50
41
X_2
42
43
47
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W
40
X_1

FIG. 2

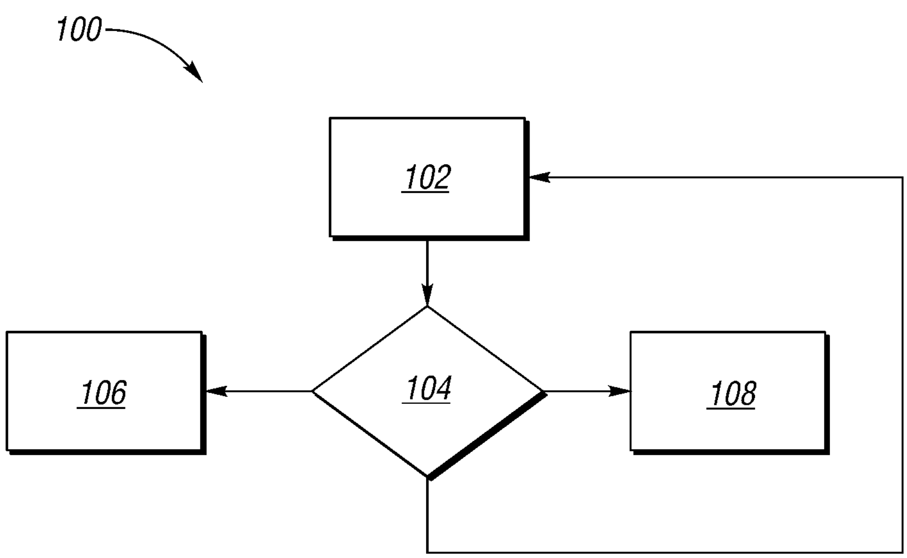

FIG. 3

METHOD AND SYSTEM FOR CONTROLLING A DEXTEROUS ROBOT EXECUTION SEQUENCE USING STATE CLASSIFICATION

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH OR DEVELOPMENT

This invention was made with government support under NASA Space Act Agreement number SAA-AT-07-003. The invention described herein may be manufactured and used by or for the U.S. Government for U.S. Government (i.e., non-commercial) purposes without the payment of royalties thereon or therefor.

TECHNICAL FIELD

The present disclosure relates to the automatic control of a dexterous robot.

BACKGROUND

Robots are electro-mechanical devices which can be used to manipulate objects via a series of links. The links are interconnected by articulations or actuator-driven robotic joints. Each joint in a typical robot represents an independent control variable or degree of freedom (DOF). End-effectors are the particular links used to perform a given work task, such as grasping a work tool or otherwise acting on an object. Precise motion control of a robot through its various DOF may be organized by task level: object level control, i.e., the ability to control the behavior of an object held in a single or cooperative grasp of the robot, end-effector control, and joint-level control. Collectively, the various control levels cooperate to achieve the required robotic dexterity and work task-related functionality.

The structural complexity of a dexterous robot is largely dependent upon the nature of the work task. During object manipulation, it is necessary to track the manipulator with respect to its environment, i.e., the system state. Without such tracking, the robot remains ignorant of the outcome of its actions during a given work sequence. However, for dexterous robots having a relatively high number of DOF, the monitoring and tracking of the system state is a highly complicated endeavor. Hundreds of individual sensor signals are commonly encountered, with difficulty arising in the processing and determination of the relevance of the various sensor signals to the ultimate determination of the present system state. Thus, existing robot control systems and control methodologies may be less than optimal when used for state tracking and monitoring of a relatively high DOF dexterous robot.

SUMMARY

Accordingly, a robotic system is disclosed herein having a dexterous robot and a controller. The robot has a relatively high number of degrees of freedom (DOF), e.g., at least 42 DOF in one example embodiment. The controller is configured to provide a tactile feedback loop that can be used to adapt an automated sequence of the robot. That is, the controller tracks the state of the robot and its operating environment during manipulation using a logic layer. The logic layer enables the robot to execute an arbitrary number of execution paths based on the outcome of the current actions. This knowledge is then used to wrap adaptive control around a given task or sequence.

The state sequence is determined during a learning phase, during which actual sensor measurements made during task execution are stored in tangible, non-transitory memory of the controller. These measurements are then processed by a Support Vector Machine (SVM). Evaluation of system state during task execution can be used by the controller as a completion condition for subsequent task steps, or to take alternative actions.

In particular, a robotic system includes a dexterous robot and a controller. The robot includes a plurality of robotic joints, actuators configured for moving the robotic joints, and sensors configured for measuring a characteristic of a corresponding one of the robotic joints, e.g., position, and transmitting the characteristics as sensor signals. The controller includes tangible, non-transitory memory on which is recorded computer-executable instructions, including a state classification module, a processor configured for executing the instructions from the tangible, non-transitory memory, classifying the sensor signals into at least two distinct classes using the state classification module, e.g., a Support Vector Machine (SVM), monitoring a system state of the robot using the classes, and controlling the robot in the execution of alternative work tasks based on the system state.

A method for controlling the dexterous robot noted above includes receiving the sensor signals using the controller, classifying the sensor signals into at least two distinct classes using the state classification module, monitoring a present system state of the robot using the classes, and controlling the robot in the execution of alternative work tasks based on the present system state.

A controller is also disclosed herein which is configured for executing the above method. The controller includes a host machine in communication with the robot, and configured for receiving the sensor signals. The controller also includes a processor and tangible, non-transitory memory on which is recorded computer-executable instructions, including the state classification module. The processor executes the instructions to thereby execute the present method as detailed herein.

The above features and advantages and other features and advantages of the present invention are readily apparent from the following detailed description of the best modes for carrying out the invention when taken in connection with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a schematic illustration of a robotic system having a controller which uses state classification data in the control of a dexterous robot during execution of a work task or sequence.

FIG. **2** is a schematic plot of parallel hyperplanes generated by a Support Vector Machine in the classification of sensor inputs within the system shown in FIG. **1**.

FIG. **3** is flow chart describing an example control approach for tracking the system state within the robotic system of FIG. **1**.

DESCRIPTION OF THE PREFERRED EMBODIMENT

With reference to the drawings, wherein like reference numbers refer to the same or similar components throughout the several views, an example robotic system **10** is shown in FIG. **1**. The robotic system **10** includes a dexterous robot **110** and a controller **24**. As will be explained in detail below with reference to FIGS. **2** and **3**, the present controller **24** is con-

figured for controlling the behavior of the robot **110** as the robot executes a given work task or sequence. The controller **24** does so in part by using state classification data generated using a state classification module **23**, for instance a Support Vector Machine (SVM) or other suitable state estimation technique.

The robot **110** shown of FIG. **1** may be configured as a humanoid in one possible embodiment. The use of humanoids may be advantageous where direct interaction is required between the robot **110** and any devices or systems that are specifically intended for human use or control. Such robots typically have an approximately human structure or appearance in the form of a full body, or a torso, arm, and/or hand, depending on the required work tasks.

The robot **110** may include a plurality of independently and interdependently-moveable compliant robotic joints, such as but not limited to a shoulder joint (indicated generally by arrow A), an elbow joint (arrow B), a wrist joint (arrow C), a neck joint (arrow D), and a waist joint (arrow E), as well as the various finger joints (arrow F) positioned between the phalanges of each robotic finger **19**. Each robotic joint may have one or more degrees of freedom (DOF).

For example, certain joints such as a shoulder joint (arrow A), an elbow joint (arrow B), and a wrist joint (arrow C) may have at least two DOF in the form of pitch and roll. Likewise, the neck joint (arrow D) may have at least three DOF, while the waist and wrist (arrows E and C, respectively) may have one or more DOF. Depending on the level of task complexity, the robot **110** may move with over 42 DOF, as is possible with the example embodiment shown in FIG. **1**. Such a high number of DOF is characteristic of a dexterous robot, which as used herein means a robot having human-like levels of dexterity, for instance with respect to the human-like levels of dexterity in the fingers **19** and hands **18**.

Although not shown in FIG. **1** for illustrative clarity, each robotic joint contains and is driven by one or more joint actuators, e.g., motors, linear actuators, rotary actuators, electrically-controlled antagonistic tendons, and the like. Each joint also includes one or more sensors **29**, with only the shoulder and elbow sensors shown in FIG. **1** for simplicity. The sensors **29** measure and transmit sensor signals (arrows **22**) to the controller **24**, where they are recorded in computer-readable memory **25** and used in the monitoring and tracking of changing system states during the execution of a given work task sequence.

When configured as a humanoid, the robot **110** may include a head **12**, a torso **14**, a waist **15**, arms **16**, hands **18**, fingers **19**, and thumbs **21**. The robot **110** may also include a task-suitable fixture or base (not shown) such as legs, treads, or another moveable or stationary base depending on the particular application or intended use of the robot **110**. A power supply **13** may be integrally mounted with respect to the robot **110**, e.g., a rechargeable battery pack carried or worn on the torso **14** or another suitable energy supply, may be used to provide sufficient electrical energy to the various joints for powering any electrically-driven actuators used therein. The power supply **13** may be controlled via a set of power control and feedback signals (arrow **27**).

Still referring to FIG. **1**, the present controller **24** provides precise motion and systems-level control over the various integrated system components of the robot **110** via control and feedback signals (arrow **11**), whether closed or open loop. Such components may include the various compliant joints, relays, lasers, lights, electro-magnetic clamps, and/or other components used for establishing precise control over the behavior of the robot **110**, including control over the fine and gross movements needed for manipulating an object **20** grasped by the fingers **19** and thumb **21** of one or more hands **18**. The controller **24** is configured to control each robotic joint in isolation from the other joints, as well as to fully coordinate the actions of multiple joints in performing a more complex work task.

The controller **24** may be embodied as one or multiple digital computers or host machines each having one or more processors **17**, read only memory (ROM), random access memory (RAM), electrically-programmable read only memory (EPROM), optical drives, magnetic drives, etc., a high-speed clock, analog-to-digital (A/D) circuitry, digital-to-analog (D/A) circuitry, and any required input/output (I/O) circuitry, I/O devices, and communication interfaces, as well as signal conditioning and buffer electronics.

The computer-readable memory **25** may include any non-transitory/tangible medium which participates in providing data or computer-readable instructions. Memory **25** may be non-volatile or volatile. Non-volatile media may include, for example, optical or magnetic disks and other persistent memory. Example volatile media may include dynamic random access memory (DRAM), which may constitute a main memory. Other examples of embodiments for memory **25** include a floppy, flexible disk, or hard disk, magnetic tape or other magnetic medium, a CD-ROM, DVD, and/or any other optical medium, as well as other possible memory devices such as flash memory.

The controller **24** includes a state classification module **23**. Module **23** may be embodied as, for example, a Support Vector Machine (SVM) or other logic layer suitable for determining the present state of the robotic system **10** from measured sensor signals (arrows **22**) as explained below. Computer-executable instructions for implementing the present method **100** may be recorded in memory **25**, and are executable by the processor(s) **17** of the controller **24** using associated hardware elements of the controller **24**. An example embodiment of the present method **100** appears in FIG. **3**, and is described in detail below.

The state classification module **23** may be embodied as a logic layer and selectively executed by the controller **24** during one or more phases of supervised machine learning, as is well understood in the art. The use of module **23** allows the controller **24** to effectively analyze data and recognize patterns presented by input data, such as the various sensor signals (arrows **22**) received from the robot **110** in the course of executing a work task or sequence.

In one embodiment, the state classification module **23** is configured as an SVM, which is also commonly described as a non-probabalistic binary linear classifier. However, those of ordinary skill in the art will appreciate that other approaches may be used without departing from the intended inventive scope. For example, the state classification module **23** may be alternatively embodied as a neural network, a logistic regression model, a Naïve Bayes classifier, a perceptron network, and a k-nearest neighbor algorithm, etc., with each term being well known in the art. The embodiment of SVM will be used hereinafter for illustrative consistency.

For each input, the SVM can predict into which of at least two data classes or categories a particular input value properly fits. Given a sufficiently large and informative set of training samples, each with an associated classification, the controller **24** can thereafter use the SVM to accurately classify each new sample of sensor signals (arrows **22**) when executing a given work sequence.

Referring to FIG. **2**, a plot **50** is shown to further explain the classification process of an SVM embodiment of the state classification module **23**. An example class could be "robot **110** holding the object **20**" of FIG. **1**. Another example class

could be "robot **110** not holding the object **20**". The x**1** and x**2** axes represent inputs from the sensors **29**, two of which are shown in FIG. **1**. Thus, in FIG. **2**, a first class is represented by cluster **40** and a second class is represented by cluster **42**.

SVM separates classes by finding values w and b, such that the line defined by the equation $w \cdot x - b = 0$ (line **43**), also referred to in the art as a hyperplane, maximizes the distance (line **47**) between the classes **40**, **42**. Note that w and x are vectors, e.g., 2-dimensional for the example depicted in FIG. **1**, and $w \cdot x$ is the vector dot product. In some cases, there can be no line $w \cdot x - b$ separating the classes. In this case, the controller **24** can apply a coordinate transformation to the sensor inputs $x=(x1, x2)$ such that the classes can be separated by a line in the transformed space, as understood in the art. Such a coordinate transformation may be used to optimize performance of the SVM approach. One possible transform is the Radial Basis Function (RBF) kernel.

The controller **24** initially may execute a training/learning phase, during which actual sensor measurements (arrows **22** of FIG. **1**) are processed by the SVM and recorded in memory **25**. The SVM first calculates a hyperplane, i.e., line **43**. Parallel lines or hyperplanes **41** and **45** are then defined by the controller **24** using respective equations ($w \cdot x - b = 1$) and ($w \cdot x - b = -1$). The values for w and b should be chosen to maximize the margin or separation between hyperplanes or lines **41** and **45** so as to minimize the chance of error in a given sensor value classification.

Referring to FIG. **3** in conjunction with the plot **50** shown in FIG. **2**, an example embodiment of the present method **100** begins at step **102** when the robot **110** of FIG. **1** executes a work task, whether in a teaching/learning phase or in the execution of an actual work task. Upon executing the task at step **102**, the controller **24** of FIG. **1** proceeds to step **104**.

At step **104**, the controller **24** records a set of sensor measurements, e.g., by recording the various sensor signals (arrows **22**) of FIG. **1** in memory **25**. The controller **24** may then process the set of sensor signals (arrows **22**) using the module **23**, for instance the SVM described above, or using any other suitable alternate predictive means.

Step **104** may entail comparing the sensor measurements to prior-recorded lasses or classifications, such as the example classes **40** and **42** shown in FIG. **2**, and then placing the measurements in one of these different classes using existing knowledge from the prior training phases. Once the system state has been properly identified, the controller **24** proceeds to steps **106** or **108**, which represent two possible divergent work tasks which may or may not be available depending on the present system state.

For example, step **106** may entail rotating the object **20** of FIG. **1** in a cooperative grasp into a predetermined position, and step **108** may entail welding the same object **20** to a stationary surface. In this hypothetical example, step **106** may only occur when the robot **110** is in a first system state, and step **108** may only occur when the robot **110** is in a second system state. Thus, proper state classification at step **104** is essential to enabling the robot **110** to transition through an arbitrary number of execution paths based on the outcome of its current actions.

While the best modes for carrying out the invention have been described in detail, those familiar with the art to which this invention relates will recognize various alternative designs and embodiments for practicing the invention within the scope of the appended claims.

The invention claimed is:

1. A robotic system comprising:

a dexterous robot having a plurality of robotic joints, actuators configured for moving the robotic joints, and sensors configured for measuring a characteristic of a corresponding one of the robotic joints, and for transmitting the characteristics as a second set of sensor signals; and

a controller configured for receiving the sensor signals, wherein the controller includes a state classification module and:

tangible, non-transitory memory on which is recorded a plurality of classes of a first set of sensor signals and computer-executable instructions for executing a first or second divergent work task from an arbitrary number of possible task execution paths; and

a processor configured for executing the instructions from the tangible, non-transitory memory to thereby cause the controller to:

receive the second set of sensor signals from the sensors;

classify the received second set of sensor signals into one of the recorded classes via the state classification module;

determine a present system state of the robot using the class of the classified received signals; and

execute the first or second divergent work task when the determined present system state of the robot is a respective first or second system state.

2. The robotic system of claim **1**, wherein the controller is configured for processing, via the processor, actual sensor measurements taken by the plurality of sensors during execution of a training phase of the state classification module.

3. The robotic system of claim **1**, wherein the state classification module is a Support Vector Machine which calculates a hyperplane or line separating the classes in an input space of the plurality of sensors.

4. The robotic system of claim **3**, wherein the Support Vector Machine selectively uses a Radial Basis Function kernel as a coordinate transformation.

5. The robotic system of claim **1**, wherein the dexterous robot is a humanoid robot having at least 42 degrees of freedom.

6. A method for controlling a dexterous robot, wherein the robot includes a plurality of robotic joints, actuators configured for moving the robotic joints, and sensors configured for measuring a characteristic of a corresponding one of the robotic joints, including a position of each joint used in the execution of a work task or sequence, and for transmitting the characteristics as a first set of sensor signals, the method comprising:

recording a plurality of classes of a second set of sensor signals in tangible, non-transitory memory of a controller having a state classification module and a processor;

receiving the first set sensor signals via the controller;

classifying the received first set of sensor signals, via the state classification module of the controller, into one of the plurality of classes;

determining a present system state of the robot using the class of the classified sensor signals; and

executing, via the controller, one of a first and a second divergent work task from an arbitrary number of possible task execution paths of the robot when the determined present system state of the robot is a respective first and second system state.

7. The method of claim **6**, further comprising:

processing, via the processor of the controller, the second set of sensor measurements taken by the sensors during execution of a training phase of the state classification module.

8. The method of claim **7**, further comprising:

calculating a hyperplane or line separating the classes in an input space of the sensors using the state classification module.

9. The method of claim **8**, wherein calculating a hyperplane or line includes using one of: a Support Vector Machine (SVM), a neural network, a logistic regression model, a Naïve Bayes classifier, a perceptron network, and a k-nearest neighbor algorithm.

10. The method of claim **9**, wherein calculating a hyperplane or line includes using the SVM, the method further comprising:

selectively using a Radial Basis Function kernel as a coordinate transformation to thereby optimize the performance of the SVM.

11. The method of claim **6**, wherein executing one of a first and a second divergent work task includes controlling a humanoid robot having at least 42 degrees of freedom through at least two alternative work tasks.

12. A controller for use within a robotic system having a dexterous robot, wherein the robot includes a plurality of robotic joints, actuators configured for moving the robotic joints, and sensors configured for measuring a characteristic of a corresponding one of the robotic joints, and for transmitting the characteristics as a second set of sensor signals, the controller comprising:

a host machine in communication with the robot, and configured for receiving the second set of sensor signals, the host machine including a state classification module; tangible, non-transitory memory on which is recorded computer-executable instructions and a plurality of classes of a first set of sensor signals; and

a processor configured for:

executing the instructions from the tangible, non-transitory memory to thereby cause the host machine to:

receive the first set of signals;

classify the received first set of sensor signals into one of the plurality of classes via the state classification module;

determine a present system state of the robot using the class of the received first set of sensor signals; and

execute one of a first or second divergent work task when the determined present system state of the robot is a respective first or second system state.

13. The controller of claim **12**, wherein the first set of sensor signals are measured by the sensors during execution of a training phase of the state classification module.

14. The controller of claim **12**, wherein the state classification module is a Support Vector Machine which calculates a hyperplane or line separating the classes in an input space of the plurality of sensors.

15. The controller of claim **14**, wherein the Support Vector Machine selectively uses a Radial Basis Function kernel as a coordinate transformation.

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